INTRA-URBAN SPATIAL DISTRIBUTIONS OF POPULATION AND EMPLOYMENT: THE CASE OF THE AGGLOMERATION OF DIJON, 1999

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Abstract

The aim of this paper is to analyze the intra-urban spatial distributions of population and employment in the agglomeration of Dijon (regional capital of Burgundy, France). We study whether this agglomeration has followed the general tendency of job decentralization observed in most urban areas or whether it is still characterized by a monocentric pattern. In that purpose, we use a sample of 136 observations at the communal and at the IRIS (infra-urban statistical area) levels with 1999 census data and the employment database SIRENE (INSEE). First, we study the spatial pattern of total employment and employment density using exploratory spatial data analysis. Apart from the CBD, few IRIS are found to be statistically significant, a result contrasting with those found using standard methods of subcenter identification with employment cut-offs. Next, in order to examine the spatial distribution of residential population density, we estimate and compare different specifications: exponential negative, spline-exponential and multicentric density functions. Moreover, spatial autocorrelation is controlled for by using the appropriate spatial econometric techniques. The spline-exponential is found to perform the best, highlighting the monocentric character of the agglomeration of Dijon.

Résumé

L'objectif de ce papier est d'analyser la distribution spatiale de l'emploi et de la population à une échelle intra-urbaine pour la COMADI en 1999. Nous étudions en particulier si l'agglomération dijonnaise a suivi la tendance générale à la décentralisation des emplois ou si elle reste caractérisée par une organisation monocentrique de l'emploi et de la densité de population. Cette étude est menée sur un échantillon de 136 unités spatiales à l'échelle communale ou intra-urbaine (IRIS) à partir de données issues du RGP et du fichier SIRENE pour l'emploi salarié du secteur privé. Dans un premier temps nous réalisons une étude d'identification des centres d'emplois en utilisant les techniques de l'Analyse Exploratoire des Données Spatiales (ESDA). En dehors du CBD, seuls quelques autres IRIS présentent un profil significatif de centres secondaires. Ce résultat montre que l'organisation spatiale de l'emploi dans la COMADI est plutôt de type monocentrique et contraste avec celui obtenu avec les méthodes standards d'identification des centres avec seuils. Ensuite, nous étudions si la distribution de la densité de population suit un schéma monocentrique ou multicentrique. Partant de la fonction de densité exponentielle négative, nous estimons différentes spécifications intégrant la distance au CBD et à d'autres centres secondaires et tenons également compte d'une forme d'hétérogénéité spatiale de type spline exponentielle négative. La présence d'autocorrélation spatiale est systématiquement contrôlée. Il apparaît que la COMADI est de nouveau caractérisée par une organisation monocentrique de la population marquée cependant par une variation du gradient de densité résidentielle entre Dijon et les communes périphériques.

Keywords: exploratory spatial data analysis; monocentric and polycentric configurations; population density; spatial autocorrelation; spatial heterogeneity; employment subcenters

JEL Classification: C21; R14

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1. INTRODUCTION

Over the last decades, there has been considerable interest in the analysis of urban spatial structure. Indeed, urban growth has exhibited complex spatial patterns including both population spread and employment decentralization from the central city towards the suburbs. The validity of the monocentric model (Alonso, 1964; Muth, 1969) to explain urban patterns has therefore been questioned since employment decentralization has recently taken a polycentric form, with a number of employment subcenters influencing the spatial distribution of employment and population. The polycentric urban phenomenon has been extensively documented for many years. Most studies have been carried out on North American urban agglomerations: Chicago (MacMillen and MacDonald, 1998a, b), Dallas-Fort Worth (Wadell and Shukla, 1993), Los Angeles (Gordon *et al.*, 1986; Heikkila *et al.*, 1989; Guiliano and Small, 1991; Small and Song, 1994; Sivitanidou, 1996), San Francisco (Cervero and Wu, 1997, 1998), Montréal (Coffey *et al.*, 1996)… Moreover, this trend toward employment decentralization is not limited to North American areas (see, for example, Alperovitch and Deutsch, 1996 for Jerusalem; Chen, 1997 for Taipei; Wu, 1998 for Guangzhou; Gaschet, 2000 for Bordeaux, Boiteux-Orain and Guillain, 2002 for Ile-de-France).

Few studies have been carried out on middle-sized urban areas. Therefore, it is interesting to investigate whether these particular areas have experienced a similar trend toward employment decentralization or whether the monocentric model is still valid to explain employment and population spatial distributions. In this paper, we are interested in this empirical challenge applied to the agglomeration of Dijon, which is the capital of Burgundy (France). Following Baumont and Le Gallo (1999, 2000), an economic center is then defined as a cluster of economic activities that influences the spatial organization of population, employment and land values. From an empirical point of view, studying polycentric rather than monocentric urban configurations raises a set of challenges (Anas *et al.*, 1998; Baumont and Le Gallo, 1999, 2000) which can be summarized as follows. How many economic subcenters can be identified apart from the traditional Central Business District (CBD)? What are their sizes and their boundaries? Does the emergence of urban subcenters result in the CBD decline? Finally, how do these multiple economic centers influence land values, population and employment distributions?

Two types of identification methods can be used in empirical studies. On the one hand, exogenous methods are based on a set of *a priori* characteristics on an economic center. Exploratory statistical and cartographic methods applied to total employment or employment densities allow the identification of a *potential set* of economic employment centers. On the other hand, endogenous methods rely on the analysis of influence: an economic employment center has a significant influence on the spatial organization of the city. Econometric estimations of population density functions, land values gradient functions or employment density functions specified with the distances from each potential economic center allow concluding if a particular economic center has such an influence.

In this paper, we apply both exogenous and endogenous identification methods combined with spatial statistic and spatial econometric techniques to study the characteristics of the agglomeration of Dijon in 1999. The study covers the territory of the *Communauté de l'Agglomération Dijonnaise* (COMADI), which is made up of 16 towns. The identification of subcenters in this area using the methods suggested by MacDonald and Guiliano and Small (McDonald, 1987; Guiliano and Small, 1991) has already been carried out in Baumont and Bourdon (2002). In this paper, we study the usefulness of an alternative identification methodology, namely exploratory spatial data analysis (Anselin, 1995, 1996; Getis and Ord, 1992; Ord and Getis, 1995) in the spirit of Scott and Lloyd W.J. (1997), which used these methods in the case of Los Angeles. Indeed, these methods allow detecting both spatial autocorrelation, in the form of spatial clusters of population and employment, and spatial heterogeneity. Furthermore, they constitute an improvement over existing methodologies that necessitate the definition of arbitrary cut-offs. Next, we analyze whether the employment clusters detected in the previous step have a significant influence on the distribution of population using both monocentric and multicentric population density functions. Given the presence of spatial autocorrelation and spatial heterogeneity in the population density distribution, this issue is investigated using the appropriate spatial econometric methods (Anselin, 1988, 2001). Indeed, the presence of spatial autocorrelation yields inconsistent and inefficient OLS estimators in population density functions. Only a few studies have used spatial econometric techniques in this framework (Griffith, 1981; Anselin and Can, 1986; Stern, 1993; Griffith and Can, 1996; McMillen, 2002).

The paper is organized as follows. In the following section, we describe the data and the spatial weight matrices used in this study. In the third section, we study the spatial pattern of total employment and employment density using exploratory spatial data analysis. In the fourth section, we provide a spatial econometric analysis of monocentric and multicentric population density functions. Different specifications are estimated and compared: exponential negative, spline-exponential and multicentric density functions. The paper concludes with a summary of key findings.

2. DATA AND SPATIAL WEIGHT MATRIX

Our study focuses on the COMADI (*Communauté de l'Agglomération Dijonnaise*), which is an urban area in the French region of Burgundy currently composed of 16 adjacent towns: the central city of Dijon (the capital of Burgundy) and 15 suburban towns around Dijon: Ahuy, Chenôve, Chevigny-Saint-Sauveur, Daix, Fontaine-lès-Dijon, Longvic, Marsannay-la-Côte, Neuilly-lès-Dijon, Ouges, Perrigny-lès-Dijon, Plombières-lès-Dijon, Quétigny, Saint-Apollinaire, Sennecey-lès-Dijon and Talant. As this urban area has its own administrative entity (*Communauté d'Agglomération*) it may be described as a *conurbation*. In terms of the zoning defined by the INSEE (i.e. the *National Institute for Statistics and Economic Surveys*), the COMADI is more than the Dijon *urban pole*[1] structuring the Dijon *urban area* (composed of 214 towns in 1999). Furthermore, we consider 22 additional suburban towns immediately surrounding the COMADI area. These towns, that we will label "urban fringe", are introduced in order to reduce edge effects present in spatial data analysis. The spatial configuration of the COMADI area and its urban fringe is displayed in Maps 1 and 2[2] and the main geographic and demographic characteristics of this area are shown in Table 1. From Table 1, it can be seen that the COMADI is a small area compared with the urban areas usually analyzed in urban studies (North American cities, major cities in Europe, Asia or in developing countries).

[Maps 1 and 2 about here]

[Table 1 about here]

We use data on employment and total population without double counting in the 1999 census. They are drawn from the RGP census and the SIRENE[3] data provided by *Direction Régionale Bourgogne de l'INSEE* for all communes in the region of Burgundy. These data are collected at the communal level and at a finer scale (IRIS-2000®) for places of more than 5000 inhabitants (cf. Appendix 1 for a description of IRIS-2000® level). Of the 16 towns that make up the COMADI, IRIS data are collected for nine of them (cf. Table 2) and none of the

[1] The towns of the COMADI correspond to the towns within the *urban pole* of Dijon plus the town of Ahuy.
[2] Maps are created using Arc-View©3.2 software on the basis of maps provided by *Direction Régionale Bourgogne de l'INSEE.*
[3] SIRENE: *Système Informatique pour le Répertoire des Entreprises et des Etablissements*.

22 urban fringe communes has IRIS data. Finally, our sample comprises 136 spatial units for which different demographic, economic and geographic data are available[4].

[Table 2 about here]

INSEE's procedures for breaking down employment or population data in the IRIS system are relatively recent and they require relevant information to be available on the localization of individuals and firms. Sometimes these localizations cannot be identified or assigned to an IRIS zone. There is therefore some discrepancy between the data provided for the whole town and the data for the town computed from the IRIS data. Such discrepancies are relatively minor, however, both for population and for employment data in our sample.

The employment data from the SIRENE files correspond to salaried employment. They relate primarily to private-sector employment and are far from complete when it comes to public-sector employment and agricultural employment as well as employment in some major financial organizations. There are a number of reasons for this: agricultural employment figures come from the farming census, public-sector employment and employment in large financial organizations cannot be broken down in the IRIS system because it is assigned for the regional head office and not for the actual place of business.

We now turn to the choice of the spatial weight matrix, which is the fundamental tool used to model the spatial interdependence between spatial units. Each unit is connected to a set of neighboring units by means of a spatial pattern introduced exogenously in this spatial weight matrix *W*. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the unit i is spatially connected to the unit j. These elements are non-stochastic, non-negative and finite. In order to normalize the outside influence upon each unit, the weight matrix is standardized such that the elements of a row sum up to one. Various matrices can be considered: a simple binary contiguity matrix, a binary spatial weight matrix with a distance-based critical cut-off, above which spatial interactions are assumed negligible, more sophisticated generalized distance-based spatial weight matrices with or without a critical cut-off.

Given the specific geographical configuration of the spatial units, we choose not to consider inverse distance matrices. Indeed, the analysis of the distance distribution between

[4] A complete list of the observations and their codes is displayed in Table 4.

all pair of units reveals that the minimal allowable cut-off[5] is above the first quartile. This particular feature is a consequence of the important size heterogeneity of the spatial units since two spatial scales are used in this study: the IRIS and the communal level. Furthermore, residential IRIS are generally much smaller than business IRIS. Therefore, the IRIS situated in the centrally urbanized areas of some subdivided communes are very small (for example in Dijon, Chenôve or Saint-Apollinaire) whereas the communes that are not subdivided are much larger spatial units and are generally located in the periphery of the Dijon. Finally, this minimal allowable cut-off is very large (almost 5 km) compared to the size of the urban area (18 km by 16 km). Therefore, if we consider such a distance cut-off, central IRIS will be connected to almost a quarter of the whole urban area, which is probably too much.

For these reasons, distance-based matrices with fixed cut-offs are not very relevant since small units in the central areas would have a lot more neighbors than the large units in the periphery. Instead, we consider two other types of weight matrices. First, we use a simple binary contiguity matrix, where an element w_{ij} is one if the units i and j share a common border, and 0 otherwise. Second, we use a k-nearest neighbors matrix computed from the distances between the units' centroids. Considering a nearest neighbors weight matrix implies that each spatial unit is connected to the same number of neighbors, wherever it is localized, and implies a variable distance cut-off for each IRIS. Therefore, we think that such a weight matrix matches the irregular spatial configuration of our urban area. The general form of the k-nearest neighbors weight matrix $W(k)$ is defined as following:

$$\begin{cases} w^*_{ij}(k) = 0 \text{ if } i = j, \forall k \\ w^*_{ij}(k) = 1 \text{ if } d_{ij} \leq d_i(k) \\ w^*_{ij}(k) = 0 \text{ if } d_{ij} > d_i(k) \end{cases} \quad \text{and} \quad w_{ij}(k) = w^*_{ij}(k) / \sum_j w^*_{ij}(k) \tag{1}$$

where $w^*_{ij}(k)$ is an element of the unstandardized weight matrix; $w_{ij}(k)$ is an element of the standardized weight matrix; $d_i(k)$ is a critical cut-off distance defined for each unit i. More precisely, $d_i(k)$ is the k^{th} order smallest distance between unit i and all the other units such that each unit i has exactly k neighbors. Since the average number of neighbors is 5.76, we use one nearest neighbor matrix with k = 6[6].

[5] i.e. the cut-off for which each unit has at least one neighbor.
[6] Complete results with k = 5 are available upon request from the authors.

3. EXPLORATORY SPATIAL DATA ANALYSIS OF EMPLOYMENT DISTRIBUTION

The identification of subcenters is often carried out using Giuliano and Small's (1991) methodology (see, for example, Giuliano and Small, 1991; Small and Song, 1994; Song, 1994; Sivitanidou, 1996; McMillen and McDonald, 1998a, b). These authors define a center as a zone or a set of contiguous zones for which a measure of employment concentration is higher than for all adjacent zones and for which the employment and employment density are above some predetermined cut-offs. The critical values chosen for these levels depend on the metropolitan area and may even vary over the metropolitan area if one observes strong variations in the employment or density employment distributions. Therefore, this identification method depends heavily on the choice of arbitrary cut-offs and may generate conflicting results. In the case of Los Angeles, for example, the various authors recognize from 6 to 54 different centers (Giuliano and Small, 1991) with only a small portion of Los Angeles' total employment actually contained within the identified centers.

Different methods have been suggested to overcome these problems and to avoid the determination of arbitrary cut-offs. For example, Craig and Ng (2001) and McMillen (2001) use nonparametric techniques. In this paper, we suggest to define a potential employment subcenter as an area having significantly higher employment and employment density than neighboring sites. To identify such areas, we use exploratory spatial data analysis (ESDA). ESDA is a set of techniques aimed at describing and visualizing spatial distributions, at identifying atypical localizations or spatial outliers, at detecting patterns of spatial association, clusters or hot spots, and at suggesting spatial regimes or other forms of spatial heterogeneity (Haining, 1990; Bailey and Gatrell, 1995; Anselin, 1998a, b). These methods provide measures of global and local spatial autocorrelation.

We apply ESDA both on total employment (Emp99) and employment density (Demp99) distributions in 1999 for the sample "COMADI + Urban fringe" of 136 observations at IRIS and communal levels. All computations are carried out for two spatial weight matrices: contiguity and 6 nearest neighbors weight matrices.

Global spatial autocorrelation

First, we consider global spatial autocorrelation, which is usually based on Moran's I statistic.

This statistic is written as follows for a row-standardized weight matrix:

$$I = \frac{z'Wz}{z'z} \tag{2}$$

where z is the vector of the n observations in deviation from the mean; $n = 136$; W is the spatial weight matrix. Values of I larger (resp. smaller) than the expected value $E(I) = -1/(n-1)$ indicate positive (resp. negative) spatial autocorrelation.

Inference is based on the permutation approach with 9999 permutations. It appears that total employment and employment density are positively spatially autocorrelated since Moran's I statistics are positive and significant with at least 5% significance level for both variables and both weight matrices (Table 3)[7].

[Table 3 about here]

Local spatial autocorrelation and Moran scatterplots

For positive global spatial autocorrelation, Moran's I global statistic doesn't allow discriminating between a spatial clustering of high values and a spatial clustering of low values. Moreover, given the definition of a potential employment subcenter used in this paper, we need to compare each zone's total employment or employment density to that of its neighbors. In that purpose, we use Moran scatterplots (Anselin, 1996), which plot the spatial lag Wz against the original values z. The four different quadrants of the scatterplot correspond to the four types of local spatial association between an observation and its neighbors: HH an observation with a high[8] value surrounded by observations with high values, LH an observation with low value surrounded by observation with high values, etc. Quadrants HH and LL (resp. LH and HL) refer to positive (resp. negative) spatial autocorrelation indicating spatial clustering of *similar* (resp. *dissimilar*) values. Note that global spatial autocorrelation may also be visualized on this graph since, from (2) Moran's I is formally equivalent to the slope coefficient of the linear regression of Wz on z using a row-standardized weight matrix.

Figures 1 and 2 display the Moran scatterplots for total employment and employment density using the contiguity weight matrix[9]. For total employment, it appears that most of the observations are characterized by spatial positive association (51.5% in quadrant LL and 16.2% in quadrant HH) while the other IRIS are characterized by negative spatial association

[7] All computations are carried out by means of SpaceStat software (Anselin, 1999).
[8] High (resp. low) means above (resp. below) the mean.
[9] Detailed results for both variables and weight matrices are displayed in Table 4.

(8.1% in quadrant HL and 24.2% in quadrant LH). Moran's scatterplot also allows visualizing the presence of outliers, i.e. the observations further than two units away from the origin. There are 7 such outliers with total employment more than two standard deviations above the mean: 2 in central COMADI (D4 and D65), 2 in South of COMADI (Co8 and Lo4), 2 in the North (D62 and D63) and one eastern IRIS (Qu5). For employment density, positive association associations are even stronger (66.2% in quadrant LL and 14.6% in quadrant HH) than those of negative spatial associations (11% in quadrant LH and 8.8% in quadrant HL). Moreover, 4 outliers with employment density more than two standard deviations above the mean are detected, all being located in central COMADI.

[Figures 1 and 2 about here]

Local spatial autocorrelation and LISA statistics

For both variables, HH spatial association may indicate an economic center covering several contiguous IRIS while the association of dissimilar values HL may indicate isolated economic centers. However, Moran scatterplots do not give any indications of significant spatial clustering. Consequently, in order to assess the significance of such spatial associations, Local Indicator of Spatial Association (LISA) statistics are computed (Anselin, 1995). The local version of Moran's *I* statistic for each observation i is written as:

$$I_i = \frac{(x_i - m)}{m_0} \sum_j w_{ij}(x_j - m) \qquad \text{with } m_0 = \sum_i (x_i - m)^2 / n \qquad (3)$$

where x_i is the observation in unit i; $n = 136$; m is the mean of the observations across spatial units and where the summation over j is such that only neighboring values of j are included. A positive value for I_i indicates spatial clustering of similar values (high or low) whereas a negative value indicates spatial clustering of dissimilar values between a zone and its neighbors.

Due to the presence of global spatial autocorrelation, inference must be based on the conditional permutation approach with 9999 permutations. The *p*-values obtained for the local Moran's statistics are then pseudo-significance levels. Note that inference is this case is further complicated by the problem of multiple comparisons since the neighborhood sets of two spatial units contain common elements (Anselin, 1995; Ord and Getis, 1995; Le Gallo and Ertur, 2003). Therefore, the overall significance of 5% is not restricted enough and we also consider significance levels at 1% and 0.1%.

Detailed results for total employment and employment density and both weight matrices are displayed in Table 4. Maps 3 and 4 display the Moran significance maps for total employment and employment density. These maps combine the information in a Moran scatterplot and the significance of LISA by showing the IRIS with significant LISA and indicating by a color code the quadrants in the Moran scatterplot to which these IRIS belong. For total employment, at the 5% pseudo-significance level, 7 IRIS are significantly HH, 3 being located in the center of the COMADI and the other 3 in the south. One eastern IRIS, that is significantly HL, can be interpreted as an isolated employment pole. However, only 3 IRIS are significant at the 1% pseudo-significance level: central IRIS Monge (D1) in HH, southern IRIS ZAC de Marsannay (Ma3) in HH and Zone Economique (Ch5) in HL. These results may indicate the existence of potential subcenters in the COMADI. However, a quite different picture is obtained when considering employment density. Indeed, in this case, only 11 central IRIS are significantly HH, possibly pointing out the monocentric character of the agglomeration. This overall picture is quite similar for 6 nearest neighbors matrix (see appendix 2).

[Maps 3 and 4 about here]

[Table 4 about here]

Concerning the identification of employment subcenters in the COMADI, these results can be interpreted as following. First, both total employment and employment density distributions are characterized by significant local positive spatial autocorrelation. The local clusters of high employment are primarily located in the inner center of the agglomeration. If total employment distribution is considered, it appears that several southern IRIS located in the South of the agglomeration can be considered as employment subcenters (i.e. the economic district of Marsannay-la-Côte and its neighborhood). Moreover, one IRIS located in the East of the agglomeration has significantly more employments than its neighbors and may be considered as an isolated economic center. However, this latter result should be considered with caution since this IRIS is surrounded by a lot of open areas. When employment density is considered, only the central IRIS are found to be statistically significant. Finally, it appears that ESDA mainly detects the central business district of the COMADI and highlights the monocentric character of the agglomeration of Dijon.

It is worthwhile to compare these results to those obtained by Baumont and Bourdon (2002) where standard subcenter identification methods have been used. Following Giuliano and Small (1991), Baumont and Bourdon define a center as a zone or a set of contiguous zones where total employment is greater than a given level $\overline{E}$ and greater than total employment in surrounding zones and where employment density is greater than a given level $\overline{D}$ and greater then the density in surrounding zones. For the urban area of the COMADI composed of 114 contiguous zones, the authors consider the employment level that allows taking into account a sufficient number of IRIS to include more than 50% of the total employment of the COMADI. This level is fixed to $\overline{E}$ = 1 400. The density employment level is $\overline{D}$ = 10 jobs per acre. Eleven IRIS containing more than 1400 jobs are identified but among them, only 5 IRIS have the sufficient level for employment density. Moreover, six other IRIS characterized by an employment density level greater than 10 jobs per acre, have more than 1 000 jobs but less than 1 400 jobs. Baumont and Bourdon (2002) named "*Employment poles*" the zone or the set of contiguous zones that have more than 1 400 jobs and named *"Potential center"* a zone that have more than 1 000 jobs whatever the level of employment density. According to these definitions, an IRIS belonging to an employment pole is a potential center. The different characteristics of these IRIS are displayed in Table 5.

[Table 5 about here]

Five employment poles have been identified. Some are composed of central IRIS, like the CBD, or of IRIS from several contiguous different towns, like the "Multi-pole" South and North. Others are single IRIS like the "Isolated Poles" Quétigny and Chevigny. Seven other IRIS are defined as potential centers and they are either centrally located or located in peripheral areas (Map 5). We note that many peripheral IRIS have many jobs although they have low employment densities. On the contrary, central IRIS have high employment densities. This is a traditional feature due to the heterogeneity of the spatial scale that we have mentioned in the preceding section. Therefore, Baumont and Bourdon (2002) prefer not considering the employment density as a relevant indicator to define economic center. According to these different results, these authors conclude that the COMADI exhibits a multicentric economic pattern for employment: the traditional CBD and four economic subcenters (South, North, Quétigny and Chevigny). This result contrasts with that found with ESDA.

[Map 5 about here]

Let us now analyze the spatial association characteristics of these economic centers with the exploratory spatial analysis that we have carried out above. Although a different sample has been used, we consider that we can compare the two studies for the following reasons. First, our sample is composed of the IRIS belonging to the COMADI and of its urban fringe. If we analyze the employment composition of the towns belonging to the urban fringe (Table 1), only 3.54% of jobs are added to the analysis. None of these towns have more than 1 000 jobs and more than 10 jobs per acre. Second, the main statistical characteristics (mean and quartiles) of the total employment and employment density distributions are quite similar in the two samples. Local spatial association indicators associated to the employment poles and potential economic centers are displayed in Table 5. We can easily note that the IRIS belonging to the CBD have significant Lisa statistics. On the contrary, the peripheral employment poles are not significant according to the ESDA except the isolated pole "Chevigny", which has to be considered with caution. Therefore, the multicentric pattern of employment highlighted by standard methods of employment subcenter identification is not fully confirmed by ESDA.

The present study and the results obtained in Baumont and Bourdon (2002) highlight some contradictory results concerning the employment pattern of the COMADI. Furthermore, two arguments make it difficult to determine the correct analysis. On the one hand, in Baumont and Bourdon (2002), the multicentric pattern is quite robust to a large variation of the employment level cut-off: at least one central IRIS and one peripheral IRIS belonging to each "Employment Pole" South and North are identified when the critical employment level varies from 1 000 jobs to 4 000 jobs. However, no statistical test assessing the significance of this result has been done. Moreover, only the restrictive definition of contiguity given by Giuliano and Small (1991) is adopted, like all the papers using this definition. On the other hand, by using ESDA, the present study allows taking into account less restrictive definitions of neighbors. Furthermore, the computation of LISA statistics uses the average total employment. In the sample, this average is 539 jobs, which is largely below the cut-off of 1 000. Therefore, what we identify as HH type IRIS are in fact IRIS having a total employment above 539 jobs and that are surrounded by other IRIS having in average total employment above 539 jobs. 22 IRIS match this definition. Following the same line of reasoning, 11 IRIS are HL type, i.e. they are surrounded by other IRIS having in average total employment below 539 jobs. However, only a few of these spatial associations are significant, with all weight matrices used.

Therefore, our study is a further contribution to the ongoing debate about exogenous identification methods. However, if we consider that an economic center influences residential location choices, we must also estimate the effects of all subcenters on population density. In that purpose, different population density functions, with different functional forms and including one or more potential economic centers, are considered in the following section.

4. SPATIAL ECONOMETRIC ANALYSIS OF POPULATION DENSITY FUNCTIONS

The analysis of urban structures is usually conducted using population residential density functions including the distance from the CBD as an explanatory factor. The negative exponential density function defined by Clark (1951) is the most used theoretical specification. It has been largely improved in order to better capture the irregularities of the population density distribution in real urban areas[10]. For example, Anderson (1982, 1985) suggests the use of cubic spline specifications when population densities do not homogeneously decrease as the distance from the CBD increases. Brueckner (1986) estimates distance-oriented density functions, with an unknown number of possible regimes, using switching regressions. Alperovich and Deutsch (2002) find evidence of two distinct regimes in the urban area of Tel-Aviv. In fact, all these studies take into account in different ways spatial heterogeneity: the estimated coefficients are different depending on their distance from the CBD or on the spatial regime they belong. Moreover, other economic centers than the CBD may influence the spatial population distribution on the urban area. In this case, the distance from several potential economic subcenters are added as explanatory variables. If more than one of the associated coefficients is statistically significant, then the urban pattern is considered as multicentric and it is considered as monocentric otherwise.

In this section, we estimate population residential density functions for the COMADI using different specifications including the distance from the CBD and from the potential economic subcenters detected in the previous section and by Baumont and Bourdon (2002). Furthermore, as for total employment and employment density, we first carry out an ESDA on population density in order to identify possible patterns of spatial heterogeneity and/or spatial autocorrelation. The latter effect should be systematically detected. Indeed, if it is ignored, the OLS estimators are inefficient and statistical inference is biased. Wrong conclusions can

[10] See Mills and Tan (1980) and McDonald (1989) for surveys of results and methodology.

therefore be drawn out of the results. Except in some isolated studies (Griffith, 1981; Anselin and Can, 1986; Stern, 1993; Griffith and Can, 1996; McMillen, 2002), spatial autocorrelation is not taken into account in the estimation of population density functions.

ESDA on population density

The population density is named Dpop99 and is defined as the population per acre. It is measured for each observation of the sample of 136 observations of the COMADI and its urban fringe. We use the same spatial weight matrices as in the ESDA on employment: the contiguity weight matrix and the 6 nearest neighbors weight matrix.

Concerning the detection of global spatial autocorrelation, the value of the Moran's I statistic is positive and significant with p = 0.001 (Table 6). This result suggests that the IRIS with relatively high values (resp. low) of population density are surrounded by IRIS with relatively high values (resp. low) of population density.

[Table 6 about here]

If we look at the spatial distribution of LISA statistics (Table 7 and Map 6), two additional features appear. First, more than 82% of the spatial observations exhibit a positive spatial autocorrelation pattern (HH and LL types). In the case of the contiguity matrix, 51 IRIS are of type HH and 61 IRIS are of type LL. Only 8 IRIS are of type HL and 16 IRIS of type LH. Second, using a pseudo-significance level of 5%, we detect clusters of high values in the central part of the COMADI and cluster of low values in the peripheral towns of the agglomeration. Note also that two clusters of high population density values are detected in the district of "Fontaine d'Ouche" (a neighborhood in Dijon) and in the town of "Chenôve". With the 6 nearest neighbors matrix, an additional cluster of high population density is found in “Le Belvédère”, a neighborhood in Talant (see appendix 2). In conclusion, this spatial autocorrelation pattern is not in contradiction with the standard theoretical distribution of residential density associated with the monocentric assumption, except for the three local peaks located at the western part of the city of Dijon that may reflect a form a spatial heterogeneity. We investigate these issues further with population density functions.

[Map 6 about here]

[Table 7 about here]

Estimation results for monocentric population density functions

Let us take as a starting point the following negative exponential function:

$$D(u) = D(0)e^{-gu+e} \qquad (3)$$

where $D(u)$ is the population density at distance u from the CBD; $D(0)$ is the population density at the CBD; g is the density gradient and measures the proportional rate at which population density falls with distance; e is the error term with the usual properties. Note that this particular form can be derived from the monocentric model with several restrictive assumptions, i.e. constant returns Cobb-Douglas production function for housing, consumer with identical tastes and incomes and unit price elasticity of demand of housing. The function is then estimated using OLS by taking logs on both sides:

$$\ln D(u) = \ln D(0) - gu + e \qquad (4)$$

All distances are measures in straight-line km from the centroid of the IRIS Monge (D1). The results of the estimation by OLS of this model are given in the first column of Table 8. The density gradient is significant at 5% and negative, $\hat{g} = -0.535$, which confirms the decay of population density from the center. Note also that the model fit is quite good: R^2-adjusted $\simeq 60\%$. Given the presence of spatial autocorrelation detected in the ESDA, we also carry out five spatial autocorrelation tests: Moran's I test adapted to regression residuals (Cliff and Ord, 1981) indicates the presence of spatial autocorrelation. To discriminate between the two forms of spatial autocorrelation – spatial autocorrelation of errors or endogenous spatial lag - we perform the Lagrange Multiplier tests: respectively LMERR and LMLAG and their robust versions (Anselin, 1988; Anselin *et al.*, 1996)[11]. It appears that both LMERR and LMLAG are significant whereas their robust versions are not. Furthermore LMERR is more significant than LMLAG. These tests therefore seem to indicate the presence of spatial error autocorrelation rather than a spatial lag variable. A direct implication of these results is that the OLS estimator is inefficient and that all the statistical inference based on it is unreliable.

Before turning to the spatial error exponential density function, we investigate the presence of some form of spatial heterogeneity given the presence of local population density peaks detected in the ESDA. In that purpose, we use a spline-exponential function as

[11] All results are presented using the contiguity weight matrix. Complete results with the 6 nearest neighbors matrix are available upon request from the authors.

suggested by Alperovitch (1995). This specification is an extension of the negative exponential function and is adapted when the population density does not decrease monotonously with distance from the CBD. One or more “knots” are specified defining distance intervals. The function is then exponential between knots and the gradient of the function is allowed to vary along different distance intervals. Note that cubic-spline functions are often used in empirical analyses. However, we prefer the use of a spline-exponential since it avoids the use of high-order distance terms and therefore limits the amount of multicollinearity (Alperovitch, 1995). We define one knot located at 4 km of the CBD because it is approximately the distance at which the three local population density peaks are situated. The spline-exponential function can then be written as:

$$\ln D(u) = \ln D(0) - gu + g_1 u_a + e \qquad (5)$$

where $D(u)$, $D(0)$, g and u are defined as before; g_1 is the parameter describing the change of the gradient of the function occurring within the distance interval defined by the 4 km knot. Finally, u_a is defined by:

$$u_a = \begin{cases} 0 & \text{if } u \leq a \\ u - a & \text{if } u > a \end{cases} \qquad \text{with } a = 4 \text{ km} \qquad (6)$$

The results of the estimation by OLS of this model are given in the third column of Table 8. While the gradient is still significant and negative, the coefficient g_1 is not significant. Therefore it seems that the gradient does not change after 4 km of the CBD. The model fit is approximately the same as in the simple exponential density function and the spline-exponential does not perform better in terms of information criteria. However, this model is strongly misspecified since the spatial autocorrelation tests indicate the omission of a spatial error and the inference based on it is not reliable.

Both models must therefore be modified to integrate spatial autocorrelation explicitly in the form of a spatial error model in order to achieve reliable inference. In equation (4) and (5), the following error structure is added:

$$e = l\,We + u \qquad u \sim N(0, s_u^2 I) \qquad (7)$$

where W is the spatial weight matrix and l is the coefficient indicating the extent of spatial autocorrelation between the error terms.

The estimation results of the exponential negative density function by maximum likelihood (ML) are displayed in the second column of Table 8. The coefficients are all strongly significant with an estimated gradient slightly lower than in the model estimated by OLS. It is as well important to note that a significant positive spatial autocorrelation of the errors is found ($\hat{l} = 0.439$). Furthermore, the LMLAG* test does not reject the null hypothesis of the absence of an additional autoregressive lag variable in the spatial error model. According to information criteria this model performs better than the preceding one (Akaike, 1974; Schwarz, 1978).

The estimation results of the spline-exponential density function by ML are presented in the forth column of table 8. Compared to the model estimated by OLS, it appears that the estimated gradient is higher and that g_1 is positive and now significant at 5%, highlighting a change of the gradient after 4 km. Others things being equal, the value of the constant term and of the absolute value of the density gradient are lower for units located farther than 4 km from the CBD ($D(0) = 3.146$ and g = -0.388) than for areas located closer than 4 km from the CBD ($D(0) = 5.062$ and g = -0.867).A significant positive spatial autocorrelation of the errors is also found ($\hat{l} = 0.509$) while the LMLAG* test does not reject the null hypothesis of the absence of an additional autoregressive lag variable in the spatial error model. According to information criteria, this model performs better than all the preceding ones.

[Table 8 about here]

All these results indicate that the monocentric model explains well the spatial pattern of population density, provided that some heterogeneity in the distance decay is allowed and that spatial autocorrelation is tested. Indeed, if spatial autocorrelation had not been tested for, we would have concluded that the spline-exponential density function was not appropriate. However, in the preceding section, a potential set of subcenters has been detected. Therefore, it is interesting to study how multicentric density functions perform compared to the monocentric model.

Estimation results for multicentric population density functions

We consider the following model:

$$\ln D(u) = \ln D(0) - g\,u + \sum_{i=1}^{m} g_i . u_i^{-1} + e \qquad (8)$$

where $D(u)$, $D(0)$, g are defined as before; u_i is the distance from subcenter *i*; g_i are the parameters associated to the subcenters to be estimated; m is the number of subcenters. All distances from subcenters are expressed in inverse form because this specification allows the effect of distance from the subcenter *i* to decline rapidly with distance. Furthermore, it limits the amount of multicollinearity (McMillen and McDonald, 1998a, b). Indeed, the maximum condition number found in the following regressions is 7.388. In this specification, a positive coefficient g_i indicates that population density falls with distance from subcenter *i*.

We consider three sets of regressions. The first one contains the distance from the 2 IRIS that were significant in ESDA on total employment: Ch5 (g_1) and Ma5 (g_2). The second one considers the subcenters that were detected in Baumont and Bourdon (2002): Ma5[12] (g_2), Qu5 (g_3) and D63[13] (g_4). The last one contains all four potential subcenters. The estimation results of these specifications by OLS are displayed in Table 9. It appears that the CBD gradient is always strongly significant and negative, highlighting the importance of the CBD, even when other subcenters are included. However, the distances from the various subcenters included are either not significant (Ch5, Qu5), or are significant but do not have the expected sign (Ma5, D63). This latter result is in contradiction with the standard conclusions of residential choice models since it indicates that population densities increase with the distance from an employment pole. Therefore, such results are not further analyzed here even if they question the nature of the attractiveness of these employment poles for residential choice. The model fits are comparable to monocentric models estimated by OLS (R^2-adjusted $\simeq 61\%$) and these specifications do not perform better in terms of information criteria. However, all three specifications are misspecified due to the omission of spatial autocorrelation, as indicated by the five spatial autocorrelation tests.

[Table 9 about here]

The inclusion of distances to various subcenters did not remove spatial autocorrelation. It is not clear, however, which spatial specification is the most appropriate. Indeed, the degrees of significance of LMERR and LMLAG are very similar in all three cases, while the robust tests are never significant. Therefore, in each case, we estimate both a spatial error and a spatial lag model.

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[12] Its centroid is taken as the centroid of the southern employment pole.
[13] Its centroid is taken as the centroid of the northern employment pole.

The latter is defined as following:

$$\ln D(u) = rW * \ln D(u) + \ln D(0) - g\,u + \sum_{i=1}^{m} g_i u_i^{-1} + e \qquad (8)$$

where W is the spatial weight matrix; $W * \ln D(u)$ is the endogenous spatially lagged variable and r is the spatial autoregressive coefficient indicating the amount of correlation between population densities of neighboring observations. The estimation results of these specifications by ML are presented in Table 10. Whatever the specification estimated, the CBD gradient is always strongly significant and negative. However, as in the preceding specifications estimated by OLS, the distances from the various subcenters are not significant or do not have the expected sign. In each case, the spatial coefficient (spatial error or spatial autoregressive) is positive and strongly significant. However, none of these models perform better in terms of information criteria than the monocentric models with spatial error autocorrelation estimated by ML.

Finally, these results show few evidence of a multicentric urban pattern in the COMADI and are in conformity with those found in the ESDA on total employment and employment density. Rather, the monocentric model allowing for some spatial heterogeneity is the most appropriate specification in the form of the spline-exponential model indicating that the density gradient is different before and after a distance of 4 km from the CBD. This distance corresponds more or less to the boundaries of Dijon where several high density housing projects were realized in the seventies. Until this distance, population densities are measured at the IRIS scale. On the contrary, beyond this distance are located peripheral residential towns often characterized by low population density levels and measured at the communal level. The spline-exponential model is then an appropriate model to capture the spatial heterogeneity in middle size agglomerations where the downtown still dominates.

[Table 10 about here]

5. CONCLUSION

In this paper, we have analyzed the intra-urban spatial distributions of population and employment in the agglomeration of Dijon (regional capital of Burgundy, France). Our aim was to study whether this agglomeration has followed the general tendency of job decentralization observed in most urban areas or whether it is still characterized by a monocentric pattern. In that purpose, a sample of 136 observations at the communal and at the

IRIS (infra-urban statistical area defined by INSEE) levels with 1999 census data and the employment database SIRENE (INSEE) was used.

First, the spatial pattern of total employment and employment density using Exploratory Spatial Data Analysis (ESDA) has been studied. Contrary to standard methods of employment subcenter identification, ESDA does not require the determination *a priori* of arbitrary cut-offs and it allows assessing the significance of clusters of high employment. The application of these procedures to total employment and employment density shows that, apart from the CBD, few IRIS are found to be statistically significant. These results contrast with those found using standard methods, where potential employment subcenters were detected in the North, South and East of the COMADI.

Second, in order to examine the spatial distribution of residential population density, different specifications have been estimated and compared. On the one hand, an exponential negative and a spline-exponential density function have been considered. The latter has been estimated due to the presence of local clusters of high population density located in the western part of the COMADI. Both functions have been found to perform quite well. On the other hand, multicentric density functions including various subcenters yield rather unsatisfactory results with distances from the subcenters that are not significant or that do not have the expected sign. In each case, spatial autocorrelation is controlled for by using spatial econometric techniques.

Finally, all the results highlight the monocentric character of the agglomeration of Dijon. Although some job decentralization, following urban policies, has taken place in the last years, there are no clusters of employment having a significant impact on the distribution of population density. These findings could be extended by considering the distribution of land and housing values and/or by studying a larger area surrounding the COMADI.

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Tables, maps and figures

Table 1: Main geographic and demographic characteristics of study area

Characteristics	COMADI	COMADI + Urban Fringe	Urban fringe/ COMADI (%)	Côte d'Or*** *(% COMADI/ Côte d'Or)*	Burgundy Region
Total area	172.4 km^2 (42 600 acres)	412.1 km^2 (101 833 acres)		8 763.2 km^2 (2%)	31 581.96 km^2 (0.5%)
Width	16 km				
Length	18 km				
Population 1999*	238 309	257 844	8.08%	504 950 (47%)	1 608 262 (14.8%)
Working pop. 1999*	111 028	120 587	8.6%	232 152 (47.8%)	708 174 (15.7%)
Employment 1999**	70 770	73 277	3.54%	125 781 (56.3%)	387 183 (18.3%)

*Sources: * Recensement Général de la Population 1999 (RGP Census)*
*** SIRENE (INSEE)*
*** Côte d'Or is the French department in Burgundy where the COMADI is located

Table 2: Towns with and without IRIS data

Towns with IRIS data	Number of IRIS	Towns with no IRIS data
Chenôve	9	Ahuy
Chevigny	5	Daix
Dijon	66	Neuilly
Fontaine	5	Ouges
Longvic	4	Perrigny
Marsannay	3	Plombières
Quétigny	5	Sennecey
St-Apollinaire	4	Urban fringe (22)
Talant	6	
Total spatial units	**107**	**29**

Table 3: Moran's *I* statistics for total employment and employment density in 1999

	Contiguity weight matrix			6 nearest neighbors weight matrix		
Variable	Moran's *I*	St. dev.	St. value	Moran's *I*	St. dev.	St. value
Emp99*	0.117	0.049	2.255	0.136	0.042	3.365
Demp99*	0.378	0.045	8.467	0.436	0.039	11.249

* The expected value for Moran's *I* statistic is -0.007 for Emp99 and Demp99. All statistics are significant at 5% level.

Table 6: Moran's *I* statistics for population density in 1999

	Contiguity weight matrix			6 nearest neighbors weight matrix		
Variable	Moran's *I*	St. dev.	St. value	Moran's *I*	St. dev.	St. value
Dpop99*	0.474	0.0494	9.734	0.367	0.043	8.771

* The expected value for Moran's *I* statistic is -0.008 for Dpop99. All statistics are significant at 5% level.

Table 4: LISA statistics for total employment and employment density in 1999

		Total employment 1999		*Employment density 1999*	
		Contiguity	***6 near. neighbors***	***Contiguity***	***6 near. neighbors***
Ahuy	***Ahuy***	LH	LH	LL	LL
	Chenôve				
Co1	Piscine-Valendons	LL	LL	LL	LL
Co2	Petignys-Chaufferies	LL	LL	LL	LL
Co3	Chapitre-Bibliothèque	LL	LL	LL	LL
Co4	Saint-Exupery	LL	LL	HL	HL
Co5	Vieux Bourg-Grands Crus	LH	LL	LL	LH
Co6	Atliers SNCF	HH	HH	HL	HL
Co7	Mairie	LH	LH	LH	LH
Co8	Zone industrielle	HH*	HL	HH	HH
Co9	STRD	HH	HH	HL	HL
	Chevigny-Saint-Sauveur				
Ch1	Breuil	LL	LL	LL*	LL
Ch2	Corcelles	LL	LL	LL**	LL*
Ch3	Centre-Ville	LL	LL	LL*	LL
Ch4	Château	LH	LH	LL	LL
Ch5	Zone Economique	HL**	HL*	LL***	LL**
Daix	***Daix***	HL	HL	LL**	LL
	Dijon				
D1	Monge	HH**	HH**	HH***	HH***
D2	Cordeliers	HH	HH**	HH**	HH***
D3	Saint Michel	LH	LH	HH	HH
D4	Grangier	HH*	HH*	HH***	HH***
D5	J-J Rousseau	HH	HH*	HH**	HH**
D6	Darcy	HH*	HH*	HH***	HH***
D7	Les Roses	LH	LH	HH	HH**
D8	République	HH	HH	HH**	HH**
D9	Clémenceau	HL	HH	HH	HH
D10	Davout	HH	HH	HH*	HH*
D11	Petit Citeaux	LH	LH*	HH**	HH**
D12	Saint Pierre	LL	LH	LH	LH
D13	Docteur Lavalle	LH	LL	HH	HH
D14	Voltaire	HL	HL	HH	HH
D15	Lyautey	HL	HL	HL	HL
D16	Parc des Sports	LH	LL	LL	LL
D17	Champmaillot	LL	LL	LH	LH
D18	Universités	HH	HL	LL	LL
D19	Lentillères	LL	LL	LL	LL
	Dijon (continued)				
D20	Petites Roches	LL	LL	LL	LH
D21	Mansart	LL	LL	LL	LL
D22	Abattoirs	LH	LH	LL	LL
D23	Castel	LH	LL	LH*	LL
D24	Stearinerie	LL	LL	LL	LL
D25	Carrousel	LL	LL	LL	LL
D26	Greuze	LH*	LL	LL	LL
D27	Arsenal	HH*	HL	LL	LL
D28	Bel Air	LL	LL**	LL	LL
D29	Larrey	LL	LL	LL	LH
D30	Bourroches Ouest	LL	LL	LL	LL
D31	Bourroches Est	LL	LL	LH	LL
D32	Trois Forgerons	HL	HL	HL	HL
D33	Les Valendons	LL	LL*	LL	LL
D34	La Montagne	LL	LL	LL*	LL
D35	Tire Pesseau	LL	LL	LL	LL
D36	Le Lac	LL	LL	HL	HL
D37	E. Belin	LL	LL	LL	LL
D38	Champ Perdrix	LL	LL	HL	HL
D39	Chartreuse	HH	HH	HH*	HH**
D40	Arquebuse	HH	HH**	HH**	HH***
D41	Tanneries	LH	LH	LH*	LH*
D42	Providence	LH	LL	LH	LL
D43	Carrières Basquin	HH	HL	HH**	HH
D44	F. Pompom	LL	LL	LL	LL
D45	Hauts Montchapet	LL	LL	LL	LL
D46	E. Spuller	LL	LL	LH	LH
D47	La Charmette	LL	LL	LL	LL
D48	Fauconnet	LL	LL	LL	LL
D49	Jouvence Ouest	LL	LL	LH	LH
D50	Jouvence Est	LL	LL	HH	HH
D51	Balzac	LH	LL	LL	LL
D52	Stalingrad	LH**	LL	LH	LL
D53	Casernes	LL	LL	LH	LH
D54	Sacré Cœur	LH	LL	LH	LH
D55	York	LH	LL	LH	LL
D56	Lochères	LH	LL	LH	LL

Notes: * 5% pseudo-significance level; ** 1% pseudo-significance level; *** 0.1% pseudo-significance level; inference based on 9999 permutations.

Table 4 (continued): LISA statistics for total employment and employment density in 1999

		Total employment 1999		Employment density 1999	
		Contiguity	*6 near. neighbors*	*Contiguity*	*6 near. neighbors*
	Dijon (continued)				
D57	Grésilles Centre	LH*	LL	LL	LL
D58	Castelnau	LL	LL	LH	LL
D59	Charles de Gaulle	LH	LL	LL	LL
D60	Concorde	HH	HL	HL	HL
D61	Clos de Pouilly	LH	LH	HL	HL
D62	La Toison d'Or	HH	HL	LL	LH
D63	ZI Nord Est	HH	HL	HL	HL
D64	La Gare	HH	HH*	HH***	HH***
D65	Le Bocage	LH	LL	LL	LL
D66	Combe à la Serpent	LL*	LL**	LL	LL
	Fontaine-lès-Dijon				
Fo1	Vieux Village	LL	LL	LL	LL
Fo2	Saverney	LL	LL	LL	LL
Fo3	Saint Martin	LL	LL	LL	LL
Fo4	Majnoni	LL	LL	LL	LL
Fo5	Activités économiques	HL	HL	HL	HL
	Longvic				
Lo1	Bief du Moulin	LH*	LH	LL	LL
Lo2	Bourg	LH	LH	LL	LL
Lo3	Parc Poussot	LH	LL	LL	LL
Lo4	Zone indust. Colombières	HH	HH	LL	LL
	Marsannay-la-Côte				
Ma1	Le Bourg	LH*	LH	LL	LH
Ma2	Champagne Haute	LL	LL	LL*	LH
Ma3	ZAC	HH**	HH**	LL	LH
Neuil	***Neuilly-lès-Dijon***	LL	LL	LL***	LL**
Ouges	***Ouges***	LH	LH	LL*	LL
Perry	***Perrigny-lès-Dijon***	HL	HH**	LL*	LH
Plomb	***Plombières-lès-Dijon***	LL	LL	LL***	LL
	Quétigny				
Qu1	Atrias-Vieux Village	LH	LH	LL	LL
Qu3	La Fontaine aux Jardins	LH	LH	LL	LL
Qu3	Les Huches	LL	LH	LL	LL
Qu4	Place Centrale	LH	LH	LL	LL
Qu5	Zone Activités Cap Vert	HL	HL	HL	HL

		Total employment 1999		Employment density 1999	
		Contiguity	*6 near. neighbors*	*Contiguity*	*6 near. neighbors*
	Saint-Apollinaire				
Sapo1	Nord Village	LH	LH	LL	LL
Sapo2	Sud Village	LH	LH	LL	LL
Sapo3	Nord-Est	HH	HH	LL	LL
Sapo4	Sud-Est	HH	HH	LL	LL
Senec	***Sennecey-lès-Dijon***	LL	LL	LL**	LL
	Talant				
Ta1	Vieux Talant-Clinique	LL	LL*	LL	LL
Ta2	Maronniers-Neruda	LL	LL	LL	LL
Ta3	Mail-Canzio-Jouvet	LL	LL	LL	LL
Ta4	Prévert-plein ciel	LL	LL	LL	LL
Ta5	Boris Vian-Triolet	LL	LL	LL	LL
Ta6	Montoillots- ZA	HL	HL	LL*	LL
	Urban fringe of COMADI				
Asn	***Asnières-lès-Dijon***	LH	LH	LL	LL
Belf	***Bellefond***	LH	LH*	LL	LL
Bres	***Bressey-sur-Tille***	LL	LL	LL	LL*
Bret	***Bretenière***	LL	LL*	LL**	LL***
Corc	***Corcelles-les-Monts***	LL	LL	LL***	LL***
Couch	***Couchey***	LL	LL	LL**	LL**
Cout	***Couternon***	LL	LL	LL**	LL**
Crim	***Crimolois***	LL	LL	LL**	LL**
Darois	***Darois***	LL	LL	LL**	LL***
Fauv	***Fauverney***	LL	LL*	LL*	LL**
Fenay	***Fénay***	LH*	LH*	LL	LL
Fixin	***Fixin***	LL	LL	LL*	LL*
Flav	***Flavignerot***	LL	LL	LL***	LL***
Hautv	***Hauteville-lès-Dijon***	LL	LL	LL**	LL*
Lant	***Lantenay***	LL	LL*	LL**	LL***
Magny	***Magny-sur-Tille***	LL	LL	LL*	LL**
Mess	***Messigny-et-Vantoux***	LL	LL	LL*	LL***
Pren	***Prenois***	LL	LL	LL**	LL***
Rouv	***Rouvres-en-Plaine***	LL	LL*	LL***	LL***
Ruff	***Ruffey-lès-Echirey***	LH*	LH*	LL	LL
Varois	***Varois-et-Chaignot***	LL	LL	LL*	LL*
Velars	***Velars-sur-Ouche***	LL	LL	LL***	LL***

Notes: * 5% pseudo-significance level; ** 1% pseudo-significance level; *** 0.1% pseudo-significance level; inference based on 9999 permutations.

Table 5: Employment poles and potential centers in 1999 detected in Baumont and Bourdon (2002) compared to LISA statistics

				Total employment 1999			Employment density 1999	
				Contiguity	*6 near. neighbors*		*contiguity*	*6 near. neighbors*
Employment poles			Emp99			Demp99a		
Name	**Characteristics**	IRIS Composition						
Inner City of Dijon	**CBD**	Monge D1	1501	HH**	HH**	28,5	HH***	HH***
		Grangier D4	4080	HH*	HH*	62,7	HH***	HH***
Total jobs: 9 644		La Gare D64	4063	HH	HH*	74,5	HH***	HH***
South	**Multi-towns**	Zone industrielle Co8	4776	HH*	HL	9,1	HH	HH
		ZAC Ma3Activités économiques	1505	HH**	HH**	2,7	LL	LH
Total jobs: 11 540		Zone indust. Colombières Lo4	5259	HH	HH	3,5	LL	LL
North	**Multi-towns**	La Toison d'Or D62	2670	HH	HL	3,1	LL	LL
		ZI Nord Est D63	5558	HH	HL	10,5	HL	HL
Total jobs: 9 634		Nord-Est Sapo3	1406	HH	HH	1,2	LL	LL
Quétigny	**Isolated pole**	Zone Activités Cap Vert Qu5	4014	HL	HL	8,8	HL	HL
Chevigny	**Isolated pole**	Zone Economique Ch5	1421	HL**	HL*	1,2	LL***	LL**
Potential center								
	IRIS Composition							
	Cordeliers D2		1048	HH	HH**	16,6	HH**	HH***
	J-J Rousseau D5		1040	HH	HH*	16,6	HH**	HH**
	Darcy D6		1200	HH*	HH	21,4	HH**	HH***
	Clémenceau D9		1164	HL	HH	39,1	HH	HH
	Voltaire D14		1061	HL	HL	10,7	HH	HH
	Fo5		1088	HL	HL	8,7	HL	HL
	Sud-Est Sapo4		1184	HH	HH	1,1	LL	LL

Table 7: LISA statistics for population density in 1999

		Contiguity	6 near. neighbors
Ahuy	***Ahuy***	LL**	LL
	Chenôve		
Co1	Piscine-Valendons	HH	HH*
Co2	Petignys-Chaufferies	HH**	HH*
Co3	Chapitre-Bibliothèque	HH*	HH*
Co4	Saint-Exupery	HH	HH
Co5	Vieux Bourg-Grands Crus	LH	LH*
Co6	Atliers SNCF	LH*	LH*
Co7	Mairie	HH	HH
Co8	Zone industrielle	LL*	LH
Co9	STRD	LL	LH
	Chevigny-Saint-Sauveur		
Ch1	Breuil	LL*	LL
Ch2	Corcelles	LL*	LL*
Ch3	Centre-Ville	HL	HL
Ch4	Château	LL**	LL
Ch5	Zone Economique	LL**	LL*
Daix	***Daix***	LL***	LH
	Dijon		
D1	Monge	HH	HH
D2	Cordeliers	HH**	HH
D3	Saint Michel	HH*	HH*
D4	Grangier	HH*	HH*
D5	J-J Rousseau	HH*	HH*
D6	Darcy	HH	HH*
D7	Les Roses	HH	HH*
D8	République	HH**	HH**
D9	Clémenceau	HH	HH*
D10	Davout	HH*	HH**
D11	Petit Citeaux	HH	HH
D12	Saint Pierre	HH	HH*
D13	Docteur Lavalle	HH	HH
D14	Voltaire	HH	HH*
D15	Lyautey	HH	HH
D16	Parc des Sports	LL	LH
D17	Champmaillot	HH	HH
D18	Universités	LL	LL
D19	Lentillères	HH	HH
	Dijon (continued)		
D20	Petites Roches	HH	HH
D21	Mansart	HL	HH
D22	Abattoirs	LL	LL
D23	Castel	LH	LH
D24	Stearinerie	HL	HH
D25	Carrousel	LH	LH
D26	Greuze	LL	LH
D27	Arsenal	LH	LH
D28	Bel Air	LH	LH
D29	Larrey	HL	HH
D30	Bourroches Ouest	HL	HH
D31	Bourroches Est	HH	HH
D32	Trois Forgerons	HH	HH
D33	Les Valendons	HL	HH**
D34	La Montagne	LL	LH**
D35	Tire Pesseau	HH*	HH**
D36	Le Lac	HH*	HH**
D37	E. Belin	HH*	HH
D38	Champ Perdrix	HH**	HH**
D39	Chartreuse	LL	LH
D40	Arquebuse	HL	HH
D41	Tanneries	HH	HH
D42	Providence	LL	LH
D43	Carrières Basquin	HH	HH
D44	F. Pompom	HL	HH
D45	Hauts Montchapet	HH	HH
D46	E. Spuller	HH*	HH*
D47	La Charmette	HH	HH
D48	Fauconnet	HH	HH
D49	Jouvence Ouest	HH*	HH*
D50	Jouvence Est	HH	HH*
D51	Balzac	HL	HH
D52	Stalingrad	HL	HH
D53	Casernes	HH	HH*
D54	Sacré Cœur	LH	LH*
D55	York	HH	HH
D56	Lochères	HH	HH

Notes: * 5% pseudo-significance level; ** 1% pseudo-significance level; *** 0.1% pseudo-significance level; inference based on 9999 permutations.

Table 7 (continued): LISA statistics for population density in 1999

		Contiguity	6 near. neighbors
	Dijon (continued)		
D57	Grésilles Centre	LL	LH
D58	Castelnau	HH	HH
D59	Charles de Gaulle	LL	LL
D60	Concorde	HL	HL
D61	Clos de Pouilly	LL	LL
D62	La Toison d'Or	LL*	LL
D63	ZI Nord Est	LL	LL
D64	La Gare	LH	LH*
D65	Le Bocage	LL	LH
D66	Combe à la Serpent	LH	LH***
	Fontaine-lès-Dijon		
Fo1	Vieux Village	LL	LL
Fo2	Saverney	LH	LH
Fo3	Saint Martin	LH	LH
Fo4	Majnoni	HL	HL
Fo5	Activités économiques	LL	LL
	Longvic		
Lo1	Bief du Moulin	HL	HL*
Lo2	Bourg	LL*	LL
Lo3	Parc Poussot	LL	LL
Lo4	Zone indust. Colombières	LL*	LL
	Marsannay-la-Côte		
Ma1	Le Bourg	LL*	LH
Ma2	Champagne Haute	LL**	LH
Ma3	ZAC	LL**	LL*
Neuil	***Neuilly-lès-Dijon***	LL**	LL*
Ouges	***Ouges***	LL**	LL*
Perry	***Perrigny-lès-Dijon***	LL***	LL**
Plomb	***Plombières-lès-Dijon***	LL***	LH
	Quétigny		
Qu1	Atrias-Vieux Village	LL	LL
Qu3	La Fontaine aux Jardins	LL	LL
Qu3	Les Huches	HL	HL
Qu4	Place Centrale	HL	HL
Qu5	Zone Activités Cap Vert	LL	LL

		Contiguity	6 near. neighbors
	Saint-Apollinaire		
Sapo1	Nord Village	LL	LH
Sapo2	Sud Village	LL	LH
Sapo3	Nord-Est	LL*	LL
Sapo4	Sud-Est	LL	LL
Senec	***Sennecey-lès-Dijon***	LL*	LL
	Talant		
Ta1	Vieux Talant-Clinique	LL	LH
Ta2	Maronniers-Neruda	LH	LH**
Ta3	Mail-Canzio-Jouvet	HH	HH**
Ta4	Prévert-plein ciel	HH	HH*
Ta5	Boris Vian-Triolet	HH	HH**
Ta6	Montoillots- ZA	LL	LH
	Urban fringe of COMADI		
Asn	***Asnières-lès-Dijon***	LL**	LL*
Belf	***Bellefond***	LL*	LL*
Bres	***Bressey-sur-Tille***	LL*	LL*
Bret	***Bretenière***	LL**	LL***
Corc	***Corcelles-les-Monts***	LL***	LL**
Couch	***Couchey***	LL***	LL**
Cout	***Couternon***	LL**	LL*
Crim	***Crimolois***	LL**	LL
Darois	***Darois***	LL**	LL***
Fauv	***Fauverney***	LL**	LL**
Fenay	***Fénay***	LL***	LL*
Fixin	***Fixin***	LL*	LL**
Flav	***Flavignerot***	LL**	LL***
Hautv	***Hauteville-lès-Dijon***	LL**	LL
Lant	***Lantenay***	LL*	LL***
Magny	***Magny-sur-Tille***	LL*	LL**
Mess	***Messigny-et-Vantoux***	LL*	LL***
Pren	***Prenois***	LL**	LL***
Rouv	***Rouvres-en-Plaine***	LL**	LL***
Ruff	***Ruffey-lès-Echirey***	LL***	LL**
Varois	***Varois-et-Chaignot***	LL**	LL**
Velars	***Velars-sur-Ouche***	LL**	LL***

Notes: * 5% pseudo-significance level; ** 1% pseudo-significance level; *** 0.1% pseudo-significance level; inference based on 9999 permutations.

Table 8: Estimation results for the monocentric density functions

	Negative exponential		Spline-exponential	
	OLS-White	**ML-error**	**OLS-White**	**ML-error**
ln *D*(0)	4.038 (0.000)	4.178 (0.000)	4.368 (0.000)	5.062 (0.000)
g **[*d(CBD)*]**	-0.535 (0.000)	-0.519 (0.000)	-0.678 (0.000)	-0.867 (0.000)
g_1 **[*d(>4km)*]**	-	-	0.208 (0.238)	0.479 (0.028)
l	-	0.439 (0.000)	-	0.509 (0.000)
R^2	0.5997	-	0.6050	-
R^2-adj	0.5967	-	0.5991	-
Sq.corr	-	0.600	-	0.600
LIK	-232.159	-225.490	-231.247	-219.656
AIC	468.318	454.981	468.494	445.313
BIC	474.143	460.806	477.232	454.051
s^2	1.806	1.552	1.795	1.481
Condition number	3.081	-	10.388	-
MORAN	4.372 (0.000)	-	4.702 (0.000)	-
LMERR	15.734 (0.000)	-	17.161 (0.000)	-
R-LMERR	1.295 (0.255)	-	4.850 (0.028)	-
LMLAG	12.945 (0.000)	-	13.110 (0.000)	-
R-LMLAG	0.129 (0.720)	-	0.798 (0.372)	-
LMLAG*	-	1.636 (0.201)	-	1.877 (0.349)
SARMA	15.862 (0.000)	-	17.960 (0.000)-	-

Notes: *p*-values are in parentheses. OLS-White indicates the use of the White (1980) heteroskedasticity consistent covariance matrix estimator for statistical inference in the OLS estimation. ML-error indicates maximum likelihood estimation of the spatial error model. Sq. Corr. is the squared correlation between predicted values and actual values. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). MORAN is the Moran's *I* test adapted to OLS residuals (Cliff and Ord, 1981). LMERR is the Lagrange multiplier test for residual spatial autocorrelation and R-LMERR is its robust version. LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable and R-LMLAG is its robust version (Anselin and Florax, 1995; Anselin *et al*., 1996). LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin, 1988). SARMA is the joint test of residual spatial autocorrelation and spatially lagged endogenous variable.

Table 9: OLS estimation results for the multicentric density functions

	Multicentric 1	Multicentric 2	Multicentric 3
	OLS-white	OLS-white	OLS-white
ln *D*(0)	4.282 (0.000)	4.819 (0.000)	4.789 (0.000)
g **[*d(CBD)*]**	-0.554 (0.000)	-0.577 (0.000)	-0.584 (0.000)
g_1 **[*d(Ch5)*]**	0.522 (0.748)	-	0.441 (0.793)
g_2 **[*d(Ma3)*]**	-1.245 (0.016)	-1.614 (0.012)	-1.581 (0.000)
g_3 **[*d(Qu5)*]**	-	0.292 (0.745)	0.225 (0.810)
g_4 **[*d(D63)*]**	-	-1.403 (0.031)	-1.390 (0.033)
R^2	0.615	0.630	0.632
R^2-adj	0.606	0.619	0.617
LIK	-229.563	-226.818	-226.511
AIC	467.126	463.637	465.022
BIC	478.777	478.200	482.498
s^2	1.764	1.708	1.713
Condition number	4.487	6.956	7.388
MORAN	3.975 (0.000)	4.091 (0.000)	3.857 (0.000)
LMERR	11.475 (0.000)	11.069 (0.000)	9.071 (0.002)
R-LMERR	0.346 (0.556)	1.237 (0.266)	0.325 (0.568)
LMLAG	11.795 (0.000)	10.018 (0.001)	9.509 (0.002)
R-LMLAG	0.666 (0.414)	0.187 (0.666)	0.762 (0.382)
SARMA	12.140 (0.002)	11.255 (0.002)	9.834 (0.007)

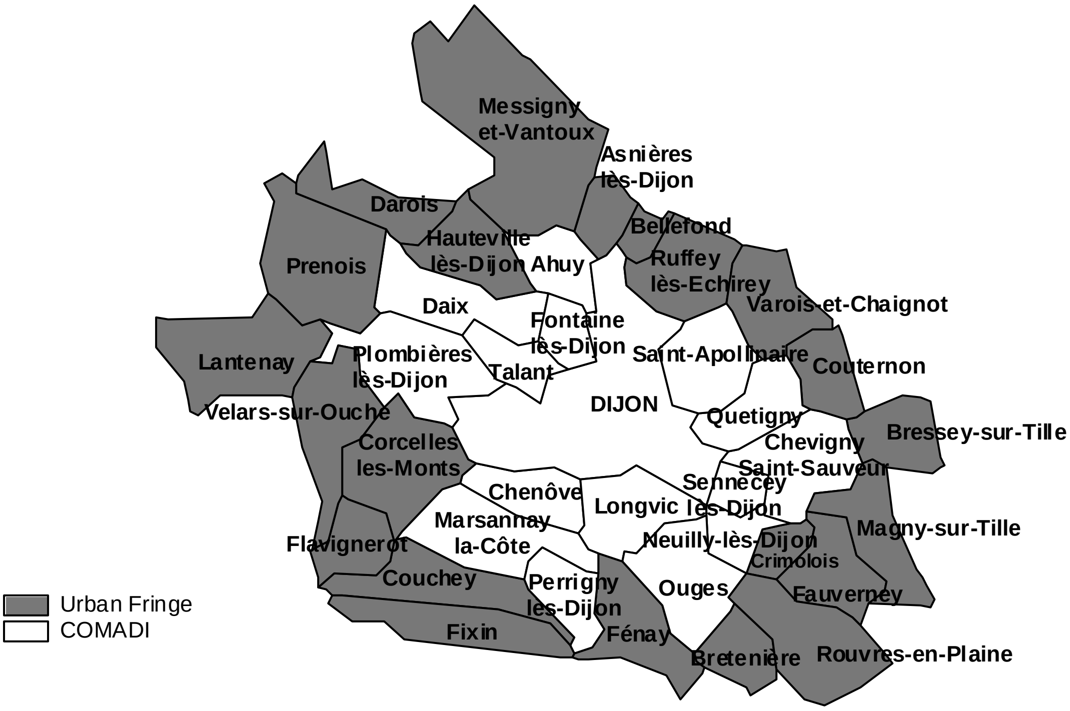
Notes: *p*-values are in parentheses. OLS-White indicates the use of the White (1980) heteroskedasticity consistent covariance matrix estimator for statistical inference in the OLS estimation. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). MORAN is the Moran's *I* test adapted to OLS residuals (Cliff and Ord, 1981). LMERR is the Lagrange multiplier test for residual spatial autocorrelation and R-LMERR is its robust version. LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable and R-LMLAG is its robust version (Anselin and Florax, 1995; Anselin *et al*., 1996). SARMA is the joint test of residual spatial autocorrelation and spatially lagged endogenous variable.

Table 10: ML estimation results for the multicentric density functions

	Multicentric 1		Multicentric 2		Multicentric 3	
	ML-err	**ML-lag**	**ML-err**	**ML-lag**	**ML-err**	**ML-lag**
ln *D*(0)	4.518	2.917	5.053	3.448	5.115	3.452
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
g **[*d(CBD)*]**	-0.528	-0.373	-0.565	-0.407	-0.561	-0.413
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
g_1 **[*d(Ch5)*]**	-0.363	0.286	-	-	-0.360	0.246
	(0.557)	(0.595)			(0.555)	(0.648)
g_2 **[*d(Ma3)*]**	-1.236	-0.965	-1.418	-1.282	-1.411	-1.269
	(0.067)	(0.103)	(0.003)	(0.032)	(0.035)	(0.035)
g_3 **[*d(Qu5)*]**	-	-	-0.212	0.186	-0.225	0.150
			(0.709)	(0.663)	(0.697)	(0.727)
g_4 **[*d(D63)*]**	-	-	-1.445	-1.148	-1.457	-1.145
			(0.032)	(0.035)	(0.032)	(0.035)
l	0.446	-	0.425	-	0.451	-
	(0.000)		(0.000)		(0.000)	
r	-	0.377	-	0.353	-	0.347
		(0.000)		(0.000)		(0.001)
Sq. corr	0.608	0.653	0.626	0.663	0.621	0.663
LIK	-223.698	-224.263	-221.497	-222.150	-221.347	-222.046
AIC	455.396	458.525	452.995	456.299	454.693	458.093
BIC	467.047	473.088	467.558	473.775	472.169	478.481
s^2	1.510	1.541	1.468	1.500	1.457	1.498
LMERR*	-	2.318	-	2.953	-	2.099
		(0.127)		(0.086)		(0.147)
LMLAG*	0.619	-	0.696	-	0.295	-
	(0.431)		(0.404)		(0.587)	

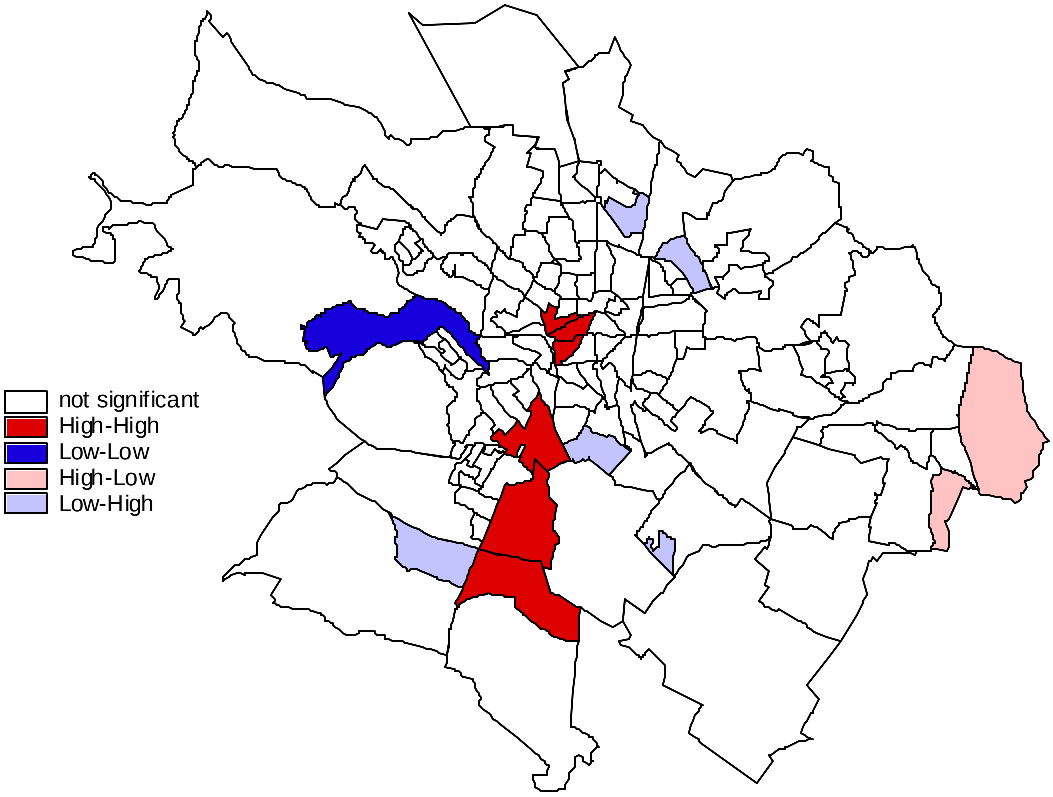
Notes: *p*-values are in parentheses. ML-err indicates maximum likelihood estimation of the spatial error model. ML-lag indicates maximum likelihood estimation of the spatial lag model. Sq. Corr. is the squared correlation between predicted values and actual values. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). LMERR* is the Lagrange multiplier test for an additional spatial error in the spatial lag model (Anselin, 1988). LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin, 1988).

Map 1: The COMADI and its urban fringe

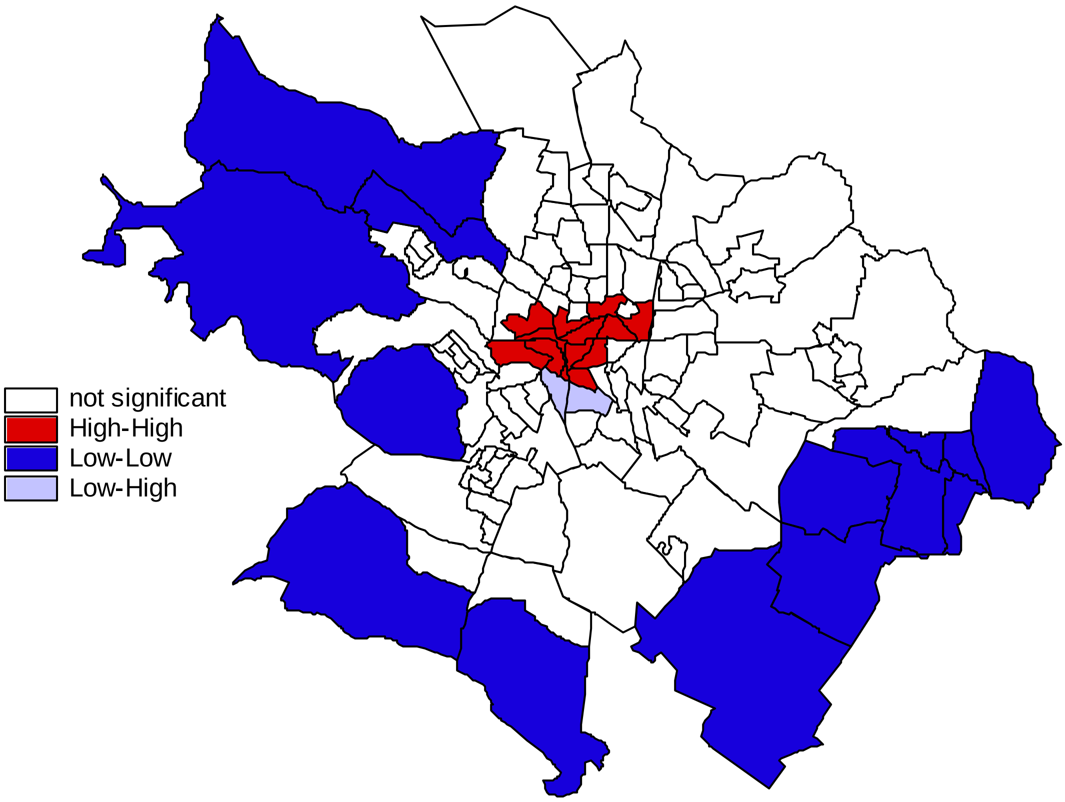


Map 2: The 114 IRIS of the COMADI

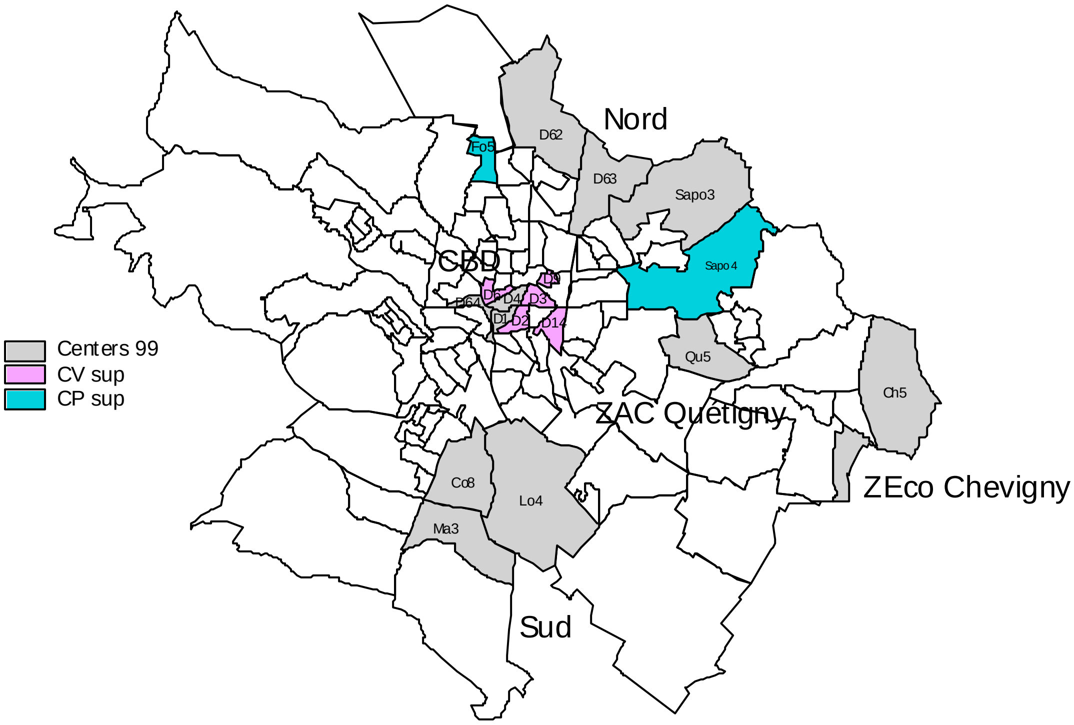
Map 3: Moran significance map for total employment 1999 (contiguity weight matrix)



Map 4: Moran significance map for employment density 1999 (contiguity weight matrix)



Map 5: Employment poles and potential centers (Baumont and Bourdon, 2002)



Centers 99: IRIS belonging to the "Employment Poles"
CV sup: Potential economic Center (1000 < Emp99 < 1400 jobs) located in Central area
CP sup: Potential economic Center (1000 < Emp99 < 1400 jobs) located in Peripheral areas.

Map 6: Moran significance map for population density 1999 (contiguity weight matrix)

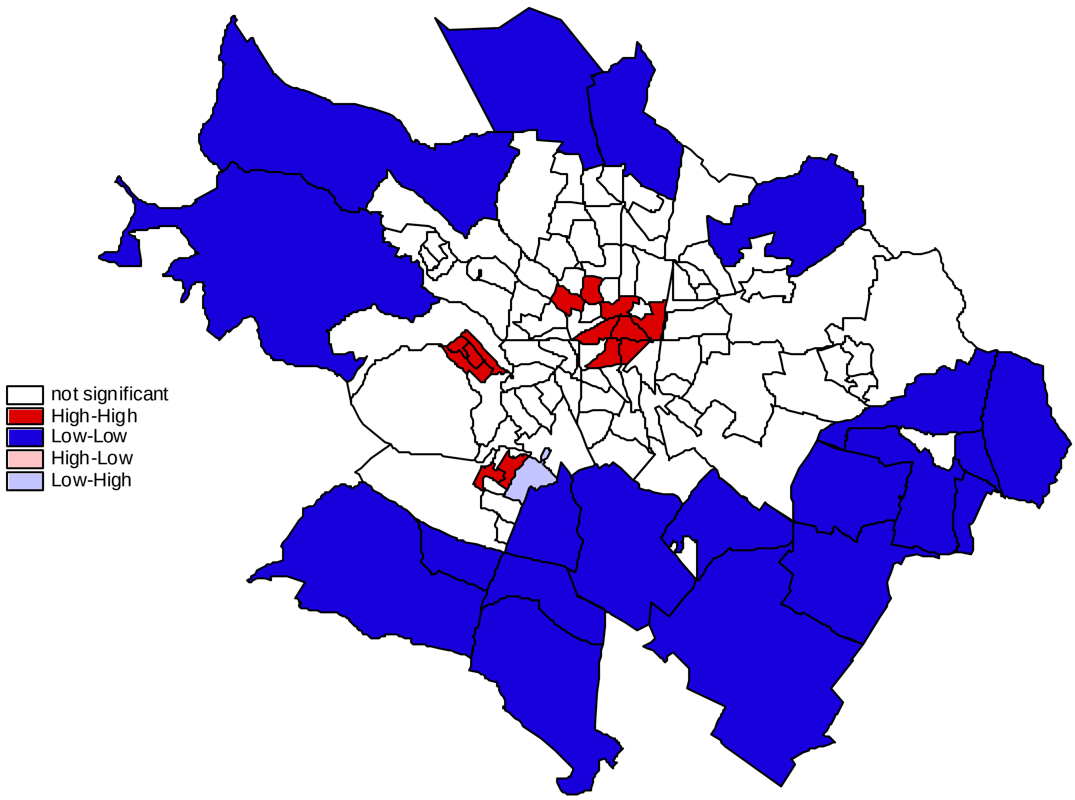


Figure 1: Moran scatterplot for total employment 1999 (contiguity weight matrix)

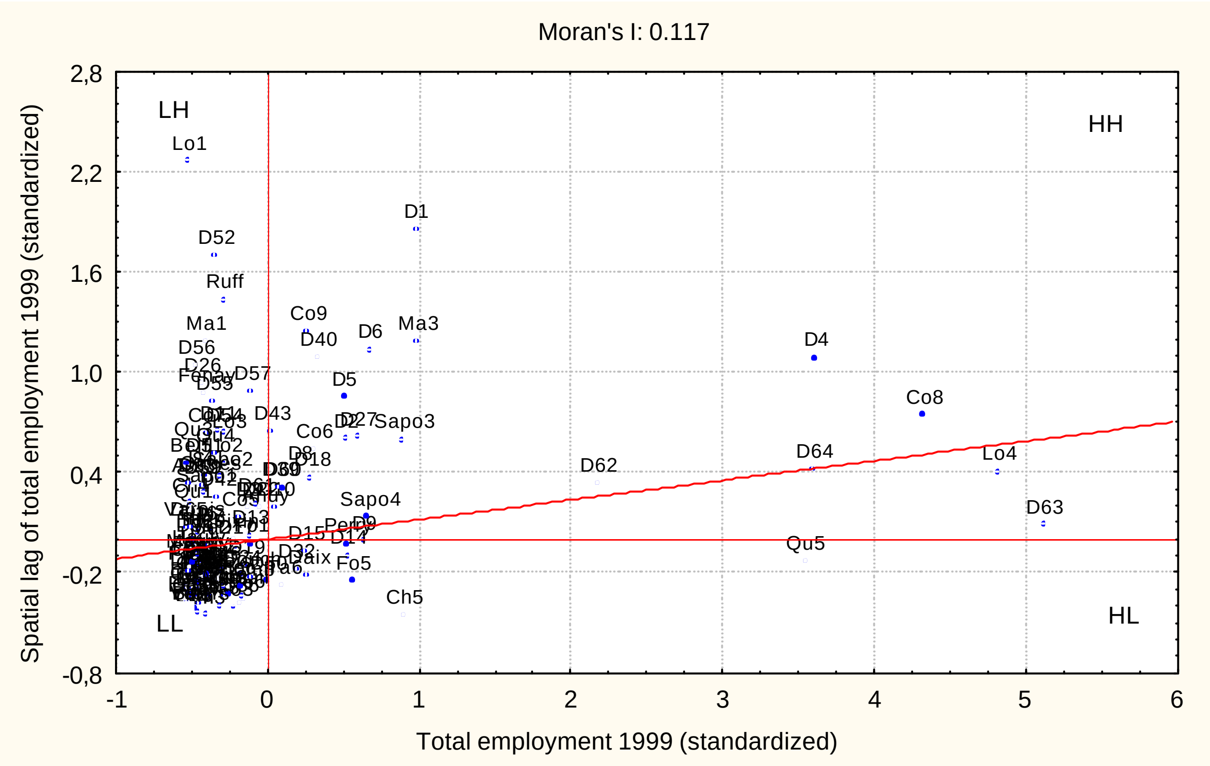
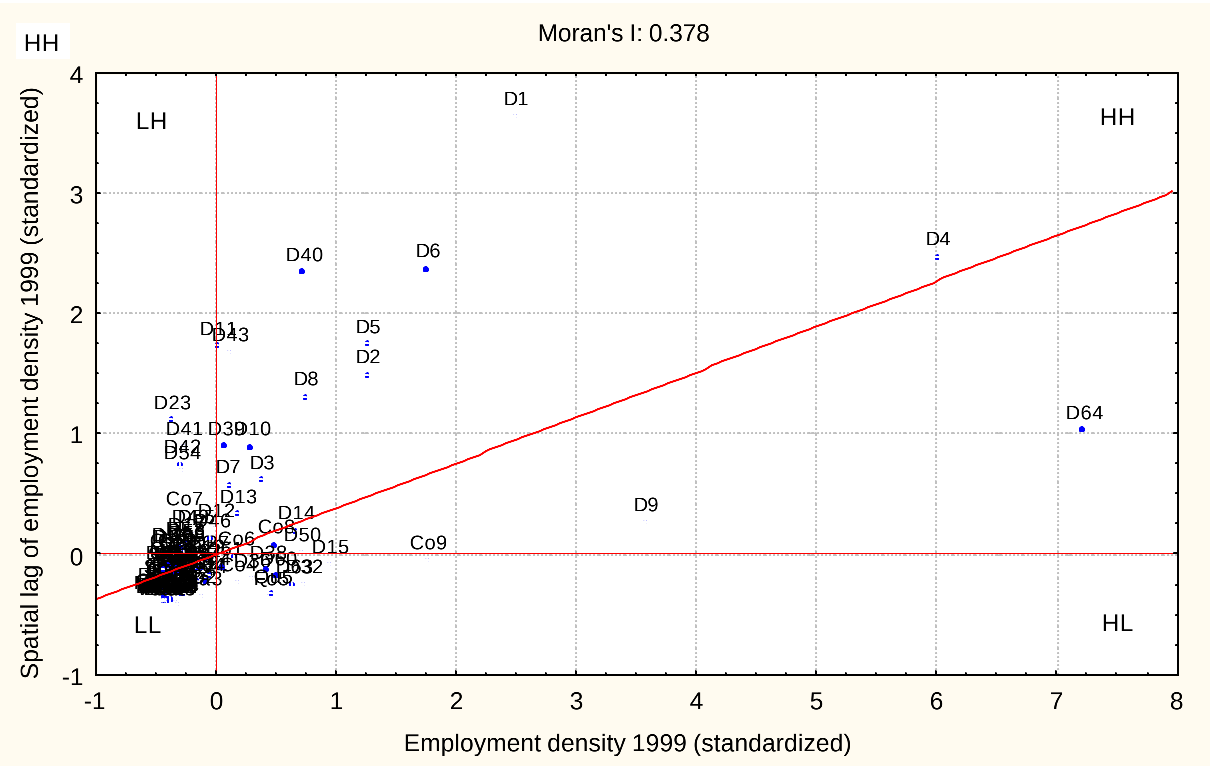


Figure 2: Moran scatterplot for employment density 1999 (contiguity weight matrix)



Appendix 1: IRIS-2000® zoning

The acronym **IRIS** stands for *Ilots Regroupés pour l'Information Statistique* (blocks clustered for statistical information)

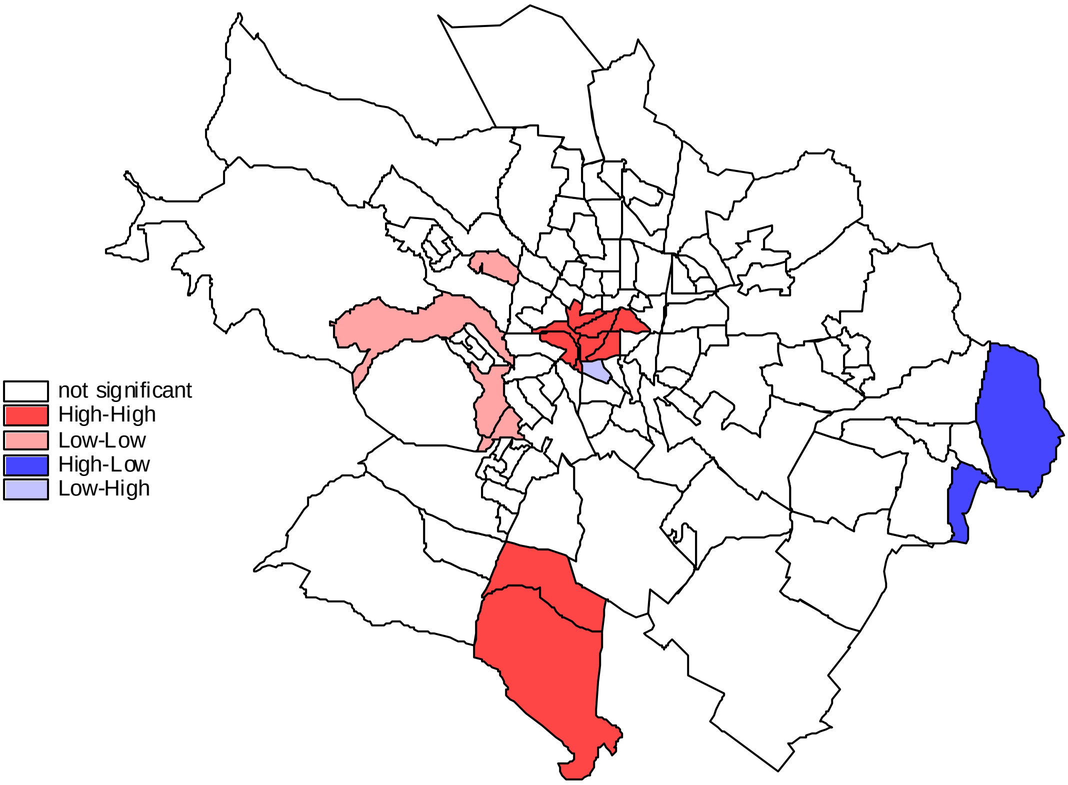
IRIS-2000® is an infra-communal level division available for all urban communes of at least 10 000 inhabitants and most communes of 5000 to 10 000 inhabitants (16 000 IRIS-2000® in France including 15 400 in metropolitan France). It is a small district, defined as a group of adjacent blocks of houses. IRIS-2000® are subdivided into three types of zone (INSEE. 2000):

- residential IRIS: IRIS-2000® with populations of 1800 to 5000 inhabitants. They are homogeneous in respect of types of housing.
- business IRIS: IRIS-2000® clustering more than 1000 employees and with twice as many salaried jobs as resident inhabitants.
- miscellaneous IRIS: IRIS-2000® covering large areas and for special purposes (woods, parkland, docklands, etc.).

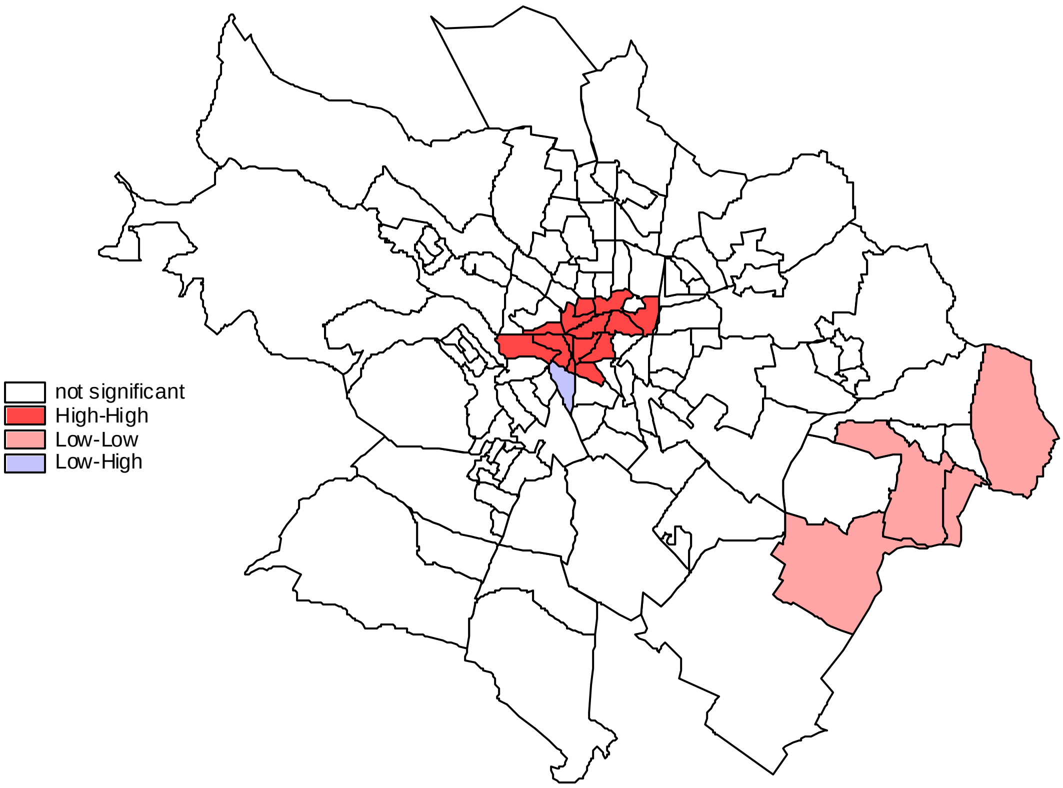
In data bases covering several communes, IRIS data correspond either to l'IRIS-2000® for subdivided communes or to the entire commune for small non-subdivided communes (34 800 communes).

Appendix 2: ESDA results with 6 nearest neighbors matrix

Moran significance map for total employment 1999



Moran significance map for employment density 1999



Moran significance map for population density 1999